DISCRETE STOCHASTIC PROGRAMMING TO ADDRESS BIOMASS YIELD VARIABILITY AND FEEDSTOCK QUALITY

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Abstract:

While advances in improving biomass yields and conversion technologies will contribute toward the U.S. energy security goals, the lack of a large-scale stable supply of feedstock could limit this biobased venture. Therefore, optimizing logistics for collecting, storing, combining feedstock, and address potential supply risks are critical to facilitate a biobased industry and offset non-renewable sources consumption. This project determined the land to contract for a five-year biomass supply subject to the risk of year to year variation in feedstock availability of two dedicated energy crops that could be blended to meet carbohydrate and ash requirements. For this purpose, I built a discrete stochastic programming model that minimized costs subject to the inherent variability of biomass yield, quality specifications, and assumed plant capacity. This research introduced a risk management approach to address the risk of year to year biomass yield variability and contributes to the creation of a market for bioenergy sources in Oklahoma.

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CHAPTER I

INTRODUCTION

Background

The February 2019 Monthly Energy Review, issued by the United States Energy Information Administration (EIA), reported 79% of the U.S. total energy consumption originates from non-renewable sources. Figure 1 shows natural gas, crude oil, and coal were the three main sources of energy consumption in the U.S. About 12% of U.S. total energy originates from renewable energy sources, distributed as 5.3% from biomass, 2.8% from hydroelectric power, 2.6% from wind, 1% from solar, and 0.2% from geothermal.

The potential of biomass to increase its footprint in the renewable energy sector has been widely studied. The U.S. Department of Energy (DOE) estimated U.S. has potentially one billion tons of dry biomass available per year from agricultural sources, forestry lands, and waste streams (DOE, 2016). The Energy Independence and Security Act of 2007 (EISA) established a national goal of 36 billion gallons/year of renewable liquid transportation fuel in the U.S. by 2022. Accordingly, the Renewable Fuel Standards policy (RFS) was created under the EISA framework as a national policy administered by the Environmental Protection Agency (EPA) to mandate that U.S.

transportation fuels contain an increasing volume of renewable fuel from conventional biofuel and advanced biofuel (Bracmort, 2018).

Conventional biofuel is any fuel produced from corn starch such as corn-starch ethanol. Advanced biofuel is produced from the cellulosic or advanced feedstock. Advanced biofuel includes biomass-based diesel and cellulosic biofuel derived from cellulose, hemicellulose, or lignin (U.S. Congress, 2007).

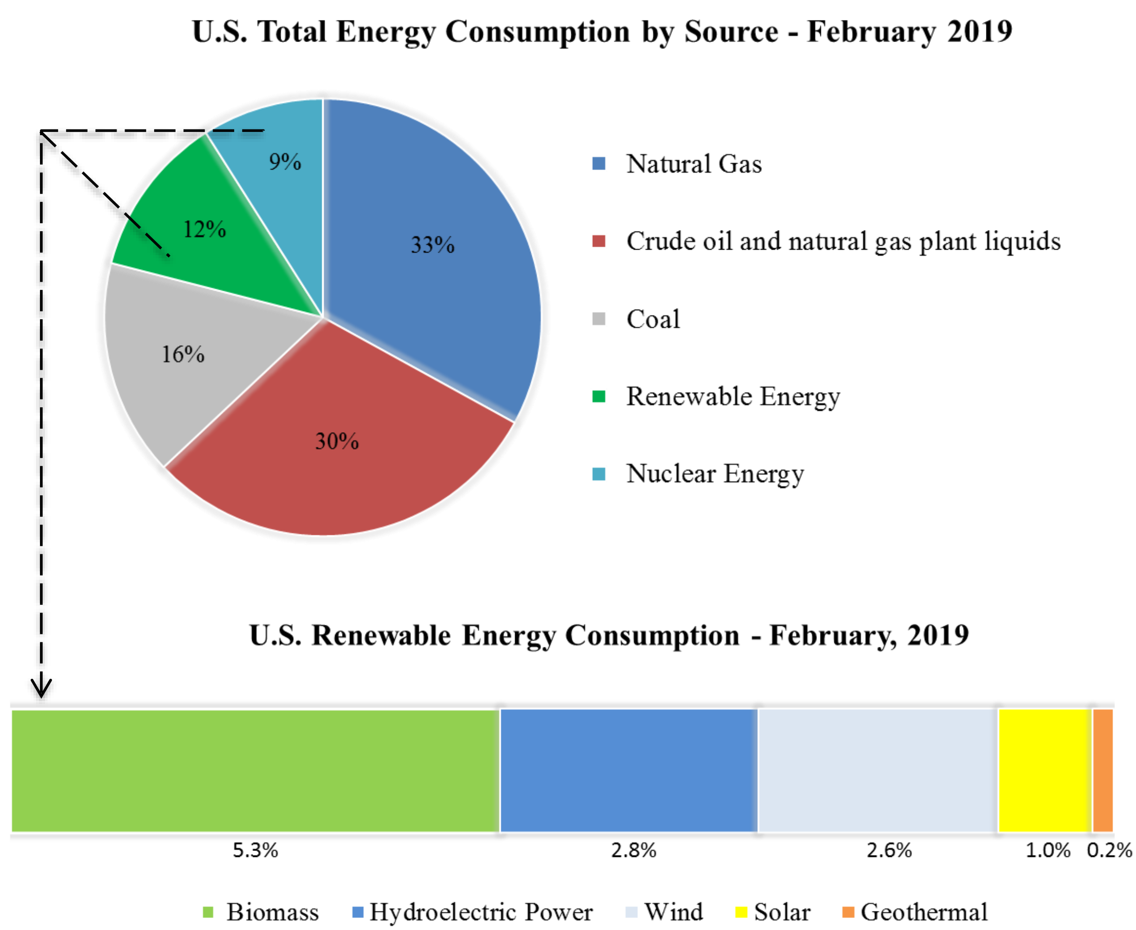

Figure 1. U.S. Total energy consumption by source and U.S. renewable energy consumption. Source: February 2019 Monthly Energy Review. EIA, 2019

Cellulosic ethanol can be produced from lignocellulosic resources such as switchgrass, miscanthus x giganteus (hereafter “miscanthus”), willow, rye, and corn stover (McKendry, 2002). In December 2018, a proposed rule under the RFS program set the biofuel requirements for 2019 as 418 million gallons for cellulosic biofuel (Bracmort, 2018). However, cellulosic ethanol production increased from 2.2 million gallons in 2015 to 3.8 million gallons in 2016 (Moriarty et al., 2018), meeting only 0.91% of the goal projected for 2019 requirements.

Strategies to increase the share of renewable energy should address limitations based on the uncertainty on biomass yield and feedstock quality. These limitations represent risk factors that hinder the creation of a local market for dedicated energy crops.

The Problem

Despite its comparative advantage for growing dedicated bioenergy crops, neither landowners nor private investors in Oklahoma have market-based incentives to encourage the allocation of resources to biomass and biofuels production respectively (Kenkel 2006; Bracmort 2018; Griffith et al. 2014). Biomass projects need to develop strategies to manage risks so investors can increase access to financial credits, and profitability.

This study focused on two problems hindering the creation of a lignocellulosic biomass-based market. First, the risk of year to year variation in feedstock availability which may cause feedstock shortage or feedstock excess based on the probability of having high or low biomass yield within years. Feedstock shortage increases the likelihood of supply disruptions and would have negative economic consequences for all stakeholders. Excessive supply increases storage costs, handling costs, and biomass loss due to degradation during storage.

Second, single crop biorefineries have certain limitations regarding biomass availability and feedstock quality inherited by the high variability of biomass (Hess et al. 2009). Variability in feedstock quality is a concern due to the impact of the physical and chemical properties on conversion process efficiency (Williams et al. 2015). Based on the current technology available to produce a biomass blend from multiple lignocellulosic feedstocks, the model is constrained to select the proportion of area that should be used to grow each one of the candidate feedstock considering carbohydrate and ash content.

While many more approaches exist to predict yields, and biomass variability has been addressed by existent literature, there are no directly usable models available in the public domain to estimate the probability model of yield variability, neither is there a model to address the embedded risk of year to year variability when planning for long-term contracts for dedicated bioenergy crops.

Research Objectives

This study evaluated the expected cost and minimum required acres for a five-year plan to supply biomass for its biochemical conversion to cellulosic ethanol. The assumed biorefinery's capacity was 724,000 tons per year, subject to the quality requirements of carbon and ash content that a lignocellulosic blend needs to meet for its biochemical conversion to ethanol, and the embedded risk of yield variability of two dedicated energy crops potentially available in Oklahoma.

The specific objectives were:

1. To determine the area of land required to grow a volume of biomass that sufficiently meets biorefinery demand, quality specifications, and minimum delivery costs.

2. To determine the minimum delivery cost of feedstock subject to the variability in yield and quality characteristics of two biomass sources, a hypothetical plant capacity, and the quality requirements to produce cellulosic ethanol.

Contribution to the literature

This research contributes to the analysis of Oklahoma's potential to create a market for biomass managing risks associated with year to year variation in potential feedstock availability, planning for long-term contracts of biomass supply to prevent operational disruptions at the biorefinery.

This research will augment the existing literature by adding the analysis for a biorefinery industry located in Oklahoma considering a blend of feedstock and not only a single crop. This will be a contribution to address the innate variability of biomass and its impact on feedstock supply for a year-long operation facility, conversion efficiency, and therefore, the biofuel total cost.

Research findings will be of interest to bioindustry stakeholders, including:

- Landowners who could potentially supply biomass.

- Potential investors interested in biofuel production using lignocellulosic biomass.
- Policymakers and regulators at the U.S Department of Energy and the U.S. Department of Agriculture, who promote the use of renewable sources of energy.

CHAPTER II

LITERATURE REVIEW

Researchers have been working on optimizing logistics for collecting, storing, and combining feedstocks to facilitate a biobased industry and offset non-renewable sources consumption. Strategies to increase the use of renewable energy sources have been considering biomass temporal and spatial availability, conversion technologies of bioresources, and the effects of feedstock variability in biofuels production. Although a considerable amount of literature underscores the importance of a large-scale feedstock supply system, there is a need to mitigate risk for investors by considering not only the potential biomass available in a region but also the uncertainty of biomass yield, and the variation in biomass characteristics.

This review presents an overview of biomass and it focuses on former strategies proposed to address logistic challenges caused by biomass availability, biomass variability, and biomass yield uncertainty.

Lignocellulosic biomass: An overview

Lignocellulosic biomass refers to plant materials containing relatively high proportions of lignin, cellulose, and hemicellulose. Woody plants, herbaceous grasses, and crop residues are lignocellulosic materials suitable for producing heat and/or electricity, second second-generation biofuels, or other bioproducts

In 2002, McKendry wrote a series of papers on energy production from biomass where he listed the general characteristics of the ideal energy crop: high yield, low energy input to produce, low cost, composition with the least contaminants, and low nutrient requirements. McKendry (2002) also examined the background to biomass production and the plant properties of interest for conversion processes such as moisture content, carbon content, ash content, calorific value, cellulose/lignin ratio, and alkali metal content. McKendry also indicated that proportions of cellulose and lignin contained on perennial grasses like switchgrass and miscanthus favor their biochemical conversion to produce liquid biofuels because these materials have a lower proportion of lignin compared with woody biomass, and a higher content of carbon present in the cellulose, needed to provide a high conversion rate of biofuel.

Wright and Turhollow (2010) published a review of several publications from the Oak Ridge National Laboratory’s Biofuels Feedstock development program which compiled the research of seven institutions in the U.S. working with different herbaceous plants. After comparing all the projects, switchgrass stood out as having higher economic potential than other crop choices but moreover, even though switchgrass was not often the crop with the highest yield, it had a lower risk to producers based on how it responded to climate variation and the relatively lower inputs needed to grow. Additionally, the authors described the environmental advantages of growing switchgrass and the need to extend the research to other dedicated energy crops.

Miscanthus has received attention more recently as a key candidate energy crop in Europe and North America. Brosse et al. (2012) published a review of the research performed to characterize different miscanthus species where miscanthus x giganteus had the highest proportion of cellulose and lignin, low mineral content, high biomass yield, and high carbon content.

The 2016 Billion-Ton Report (BT16) evaluated the potential economic availability of dedicated biomass energy crops and identified perennial grasses such as switchgrass and miscanthus as potential biomass source candidates. Among lignocellulosic materials, both switchgrass and miscanthus present interesting features, combining high yields with low inputs, and the potential of turning marginal land in profitable rural areas, but despite the extensive research available for switchgrass and miscanthus, most cellulosic biorefineries have focused primarily on corn stover (DOE, 2016).

Potential lignocellulosic biomass available

In the BT16, DOE estimated one billion tons or more of potential biomass resources per year in the United States combining used biomass at that time and biomass potentially available from 2019 to 2040. BT16 used publicly available data from USDA and the Policy Analysis System (POLYSYS) to quantify the potential biomass resources under a base-case scenario and a high yield scenario, with a 3% yield improvement. The projected supply was estimated such that all projected demands for food, feed, fiber, fuel, forest products, and exports were satisfied before biomass crops are planted. The same report modeled a production-target simulation of 250 million tons by 2022 with an assumed price of $60 per dry ton in 2020, which resulted in a potential nationwide supply available of 93 million tons of miscanthus and 64 million tons of switchgrass, 132 million tons of primary residues, 28 million tons of coppice woody, and 1.5 millions of energy cane (DOE, 2016).

A few years before the BT16 was released, EPA (2010) used the Forestry and Agriculture Sector Optimization Model (FASOM) to project 913 million gallons of cellulosic ethanol produced by 2022, distributed in the states of Oklahoma (777 million gallons), West Virginia (101 million gallons), and New Hampshire (35 million gallons). To calculate the projected production of cellulosic ethanol, EPA estimated potential biomass available in a radius of 100 miles or less from the proposed biorefineries. Based on the results, 85% of the switchgrass was projected to be likely grown in Oklahoma, assuming a majority of acres will come from replacing wheat and hay. Furthermore, EPA also located potential cellulosic ethanol facilities in 8 Oklahoman counties with the following projected production capacities in million gallons per year: Craig 130, Grady 108, Hughes 91, Kingfisher 110, Lincoln 120, Muskogee 118, and Osage 116.

EPA (2010) assumed 80 gallons of ethanol can be produced from one ton of feedstock, therefore, the total feedstock projected to be available for those biorefineries is a little less than 10 million tons of switchgrass.

Haque et al. (2014) built a multi-region, multi-period, mixed integer mathematical programming model to maximize the net present value (NPV) of the cost to grow, harvest, store and transport switchgrass to an optimally located set of biorefineries. The mathematical programming model was solved first for a single biorefinery, then for two biorefineries and so on until nine biorefineries were located simultaneously in the study region. Each plant was assumed to process 1,483 tons of switchgrass biomass per day, delivered as large rectangular solid bales, and transported by truck from the field to the plant. Under the assumptions followed by Haque et al. (2014), there is enough biomass available in Oklahoma to meet the demand of nine biorefineries capable to process 4.8 million tons per year, which is half of the biomass projected by EPA (2010). The estimated cost to deliver switchgrass to one single biorefinery optimally located in Grady, Oklahoma was 50 $ per ton. One limitation of this research is assuming that 10% of the cropland and 10% of the improved pasture land would be available for conversion to switchgrass, which is an arbitrary percentage subject to change based on the willingness of farmers to adopt energy crops. Another limitation is that biomass yield variability was not considered, nor the excess of biomass that may be stored to be used in later years to compensate for low yield periods.

Biomass availability is a decisive factor to consider when designing a supply chain and selecting optimal biorefinery locations, nevertheless, it is not the only factor to be explored. As seen in figure 2, even though EPA and the BT16 projected one billion tons of biomass potentially available in the U.S., cellulosic ethanol is currently produced mainly from corn starch. Based on the 2020 Ethanol Industry Outlook, only 0.5% of the ethanol produced in the U.S. uses exclusively cellulosic biomass as feedstock, and 3.4% uses a combination of corn, sorghum, and cellulosic biomass. Currently, these plants are located in the states of Iowa, Kansas, California, Wisconsin, and Florida.

Up to this date, no cellulosic biofuel plants are operating in Oklahoma, regarding its potential to produce 85% of U.S. cellulosic ethanol from switchgrass according to

EPA (2010). Figure 3 presents Oklahoma energy production estimates by the end of the year 2017.

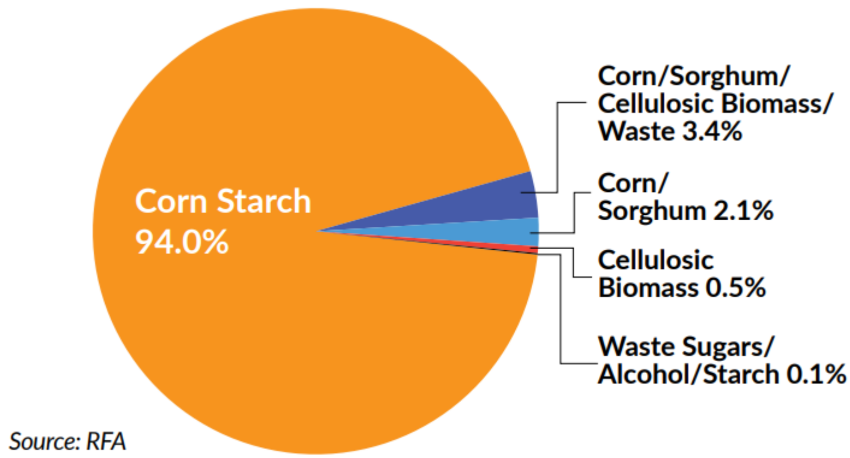

Figure 2. U.S. Ethanol production by feedstock type. Source: RFA. Available at: https://ethanolrfa.org/wp-content/uploads/2020/02/2020-Outlook-Final-for-Website.pdf

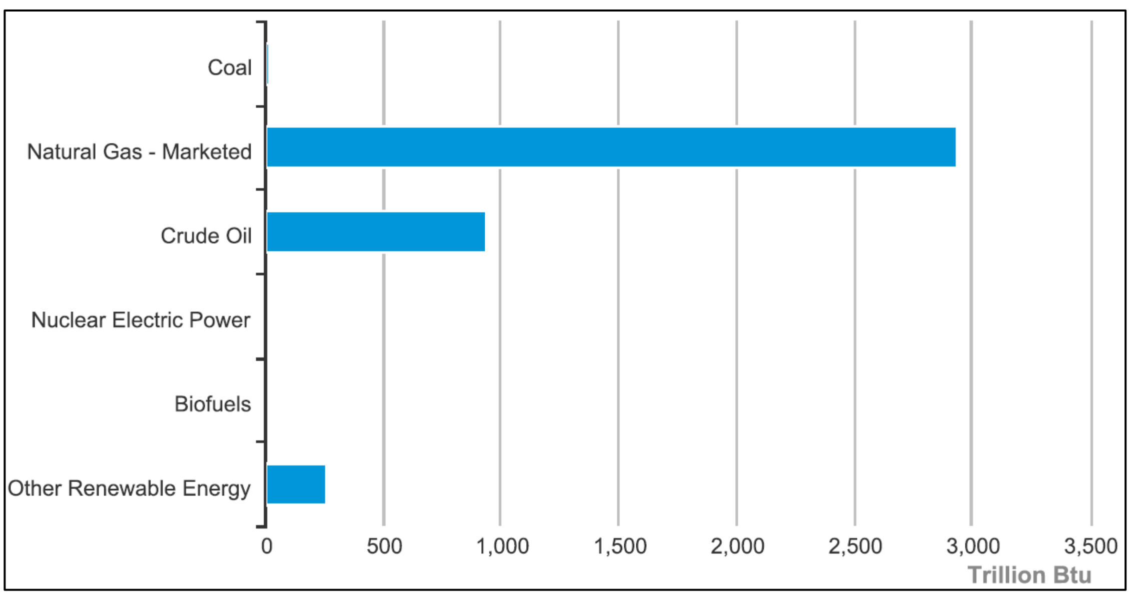

Figure 3. Oklahoma energy production estimates, 2017. Source: EIA. State Energy Data System. 2019. Oklahoma Energy Production Estimates, 2016. Available at: https://www.eia.gov/state/?sid=OK#tabs-3

Lignocellulosic biomass yield variability

Debnath et al. (2014) considered the spatial and temporal variability of switchgrass yield to determine the optimal leasing scheme for a biorefinery with a capacity of 2,200 tons per day. For this purpose, the authors simulated switchgrass yield for 50 years based on historical weather data from 1996 to 2011 using a calibrated biophysical simulation model and constructed three mathematical programming models to determine the optimal quality, quantity, and location of land to lease. The first model used the average yield as the production yield for all periods and identified the biorefinery would have to stop operations for an average of 29.5 days during half of the 50 years due to insufficient biomass. The second model located the least-cost quantity of land needed to guarantee a supply of 771,617 tons per year. The results in table 1 showed the quantity of land increased compared with model 1, and the increase in cost could be interpreted as the annual cost of a self-insurance policy to prevent idling the biorefinery due to insufficient feedstock. The third model was performed under different scenarios varying storage losses and storage costs to consider the cost of storing the excess production for its use in later years. Table 2 showed the results for an assumed storage loss of 15% and the highest storage cost. In conclusion, the strategy to lease sufficient land for the worst-case production year, and to harvest only what is required for the year, resulted in an average cost of delivered feedstock 0.3 % greater than the strategy to harvest all biomass produced in each year and store any excess for use in future years. Debnath et al. (2014) research was limited to a single feedstock, and the yield variability was introduced in the model based on historical data following a set sequence year after year.

The BT16 considered three different high yield scenarios with an annual year variation of 2%, 3%, and 4% in the 2015-2040 simulation period (DOE, 2016), hence it built three different scenarios, but it didn't consider a scenario with a low yield year followed by a high yield year, instead, the models considered a constant rate of yield increase.

Table 1. Total annual feedstock costs (land rent, production, fertilizer, harvest, and transportation), the average cost to deliver switchgrass, area leased, and average yield per harvested acre.

	The average cost to deliver switchgrass ($/Ton)	Total feedstock costs ($/year)	Land Contracted (Acres)	Average yield per harvested Acre (Ton/Acre)
The result from model 1				
Average yield	54.49	42,049,000	123868.79	6.25
The result from model 2: Insure 771,617 Ton in every state of nature				
Average	58.21	44,919,000	123609.33	6.25
Best yield year	56.97	43,960,000	104982.56	7.36
Worst yield year	60.94	47,026,000	149478.76	5.17

[a] Based on 50 years of weather data from 1962 to 2011
Source: Debnath et al. (2014)

Table 2. Switchgrass cost and land area required to provide 717,617 tons per year for a 15% of storage loss and a storage cost of 16.33 $ per ton

Storage cost ($/Tons)	Total feedstock costs ($/year)	The average cost of delivered biomass ($/Tons)	Area leased and harvested (acres)
16.33	46,252,120.00	59.94	125,346.48

Source: Debnath et al. (2014)

Variability in lignocellulosic biomass characteristics

Biomass characteristics are highly variable due to species variability, production, harvest, collection, and storage methods.

Kenney et al. (2013-a) identified feedstock quality as one of the limitations not being addressed by supply systems designed up to that date and proposed the implementation of a dockage fee system based on the costs that biorefineries would have to incur to process off-spec material, so biorefineries could benefit from a more standardized feedstock and farmers would be penalized and be accountable for establishing quality controls and handling practices to meet the biomass specifications. The authors established biomass specifications targets as moisture below 20%, ash content below 5%, and carbohydrate content above 59%. The authors recognized the challenge to meet these targets, therefore they presented a multi-feedstock approach via a blended feedstock strategy where "…multiple feedstocks were blended in specific ratios determined by availability, access cost (grower payment), and composition. Recent supply chains have evolved to advanced feedstock supply systems which can use multiple sources of biomass and implementing advanced preprocessing technologies to obtain a conversion-ready feedstock, which would be a more flexible and attractive scenario for both farmers and biorefineries.

Based on Kenney et al. (2013-a), moisture does not have a significant, direct cost implication in a biochemical process, which was a reference to prioritize carbohydrate and ash specifications.

Kenney et al. (2013-b) evaluated biomass variability associated with ash content, carbohydrate content, particle morphology, and moisture. Their research reported a mean ash content for miscanthus of 3.3 %, with samples varying within a range from 1.1 to 9.3%. The authors also reported a mean ash content for switchgrass of 5.8%, with samples varying within a range from 2.7 to 10.6%. In general, herbaceous feedstocks exhibited higher ash content and higher variability in their composition when compared with woody biomass.

Table 3. Mean ash content values and ranges for selected lignocellulosic biomass feedstocks

Feedstock	Mean ash (%)[a]	Reported range (%)
Miscanthus	3.3 (13)	1.1 – 9.3
Switchgrass	5.8 (21)	2.7 – 10.6

Source: Kenney et al.-b (2013)
[a]Mean value presented with the number of reported samples in parenthesis.

Williams et al. (2015) conducted a study exploring the different sources of biomass variability where data presented high variability associated with harvest season and year as observed in table 4.

Excessive ash reduces the conversion yield by displacing valuable carbohydrate content, increases operational costs by increasing wear in handling and feeding equipment, and increases waste cost disposal (Kenney et al. 2013-b, Williams et al. 2015).

In data collected by Kenney et al. (2013-b) carbohydrate content in miscanthus exhibited a mean value of 61% within the range of 55% to 65%. Miscanthus also exhibited lower moisture and lower ash concentrations than other lignocellulosic biomass crops.

Based on a more recent study by Roni et al. (2020), lower carbohydrate content negatively impacts sugar yields which results in lower ethanol yields, and it has been given more importance than ash content when selecting biomass sources. Data presented by the authors indicated that switchgrass samples presented carbohydrate contents above 59%. Under a blended feedstock approach, miscanthus could be mixed with switchgrass and/or corn stover to reduce final ash content and compensate the lower carbohydrate content to meet quality specifications.

Table 4. Ash content variation in switchgrass by harvest season and year

Season and year	Mean total ash (%)
Fall (2007-2010)	9.31
Spring (2007–2010)	8.67
Fall (2001–2005)	3.46
Spring (2001–2005)	2.26
(2000)	5.2
(1999)	7.2
(1998)	6.3

Source: Williams et al. 2015

Blended feedstock approach

The INL has studied possible strategies to overcome the challenges of supplying a uniform quality material at a minimum cost for the stable operation of a biorefinery. Design cases have been adjusting from single feedstock systems to multiple feedstock supply chains able to provide a uniform, quality-controlled, and economically feasible conversion-ready feedstock. The Idaho National Laboratory (INL) proposed the

Advanced Uniform-Format Design (AUFD) to produce a standardized blend from available lignocellulosic biomass. In the AUFD, agricultural residues and biomass energy crops can be transported from the farmer's gate to a central depot where they can be processed to produce a conversion-ready feedstock that will meet quality specifications of the conversion process (Hess et al., 2009).

According to Hess et al. (2009): "The Advanced Uniform system changes biomass of various types (i.e., corn stover, switchgrass, etc.) and physical characteristics (i.e., bulk densities, moisture content, etc.) into a standardized format early in the supply chain. This uniform material format allows biomass to be handled as a commodity that can be bought and sold in a market, vastly increasing its availability to the biorefinery and enabling large-scale facilities to operate with a continuous, consistent, and economic feedstock supply. The commodity-scale system also removes the obligation for local farmers to contract directly with the biorefineries for biomass feedstocks."

Blending is a common practice in grains and sugar, performed to meet the quality requirements of the end-user. The effects of feedstock blending have been studied, with results indicating that blending decreases the uncertainty in conversion performance by producing a more uniform quality feedstock (Ou et al., 2018). Based on this approach, the single feedstock design, as performed in previous literature, was modified to consider multiple lignocellulosic resources based on temporal and spatial availability, quality requirements, and supply and demand volumes.

Kenney et al. (2013-a) considered a blended feedstock strategy where multiple feedstocks are blended in specific ratios determined by availability, grower payment, and composition. A blend of 60% corn stover, 35% switchgrass, and 5% municipal solid waste resulted in a cost 30% lower than the access cost of corn stover alone.

Based on a case study for a biorefinery located in Kansas, Roni (2018) determined that a blend of 48.2% miscanthus, 29.4% switchgrass, 18.6% two-pass corn stover, and 3.8% grass clippings would meet both carbohydrate (59%) and ash specifications (less than 5%). These results were obtained after solving a mixed-integer linear programming model to determine the least-cost blend from a set of candidate feedstocks. The plant capacity assumed was 1,988 dry tons per day. The costs estimated that add up to $115.52 per ton for the least-cost blend are listed in table 5.

Table 5. Least-cost blend of corn stover (18.61%), switchgrass (29.40%), miscanthus (48.20%), and grass clippings (3.78%)

Cost item		Cost ($/ton)
Grower payment	…….	46.19
Transportation and handling	…….	16.67
Other logistics cost	…….	52.66
Total delivery cost	…….	115.52

Source: Ronni et al. (2018). INL

Our research addresses the limitation of the previous literature by considering yield variability, stored biomass for future years, variation in the multiple feedstock characteristics to determine the optimal land leasing scheme for a five-year contract. I also calculated the probability of either a low yield scenario or a high yield scenario to addressed yield variability with a probability model and a stochastic optimization model, in addition to the constraints that addressed yield characteristics variability.

The main hypothesis of this research is that costs can be reduced by introducing the probability model to control for the risk of yield variability and the differences in the biomass quality characteristics. Also, a plan to assign the proportion of biomass needed from each crop that considers the blending approach could be another strategy to manage supply chain risks.

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CHAPTER III

METHODOLOGY

Given biomass yield uncertainty, planning for long-term contracts for dedicated bioenergy crops is an embedded risk problem that can be solved through discrete stochastic programming. The proposed methodology unfolds in the following steps. First, I applied the method of Gaussian Cubature to calculate the set of values and probabilities for the first stage states of nature (DeVuyst and Preckel, 2007). Second, following the approach defined by Rae (1971), I built a probability model to define the number of stages, the possible random events called states of nature, and the joint probabilities considering the sequence of states of nature that may occur by the end of the last stage. The third step was to model a discrete stochastic optimization problem to minimize the feedstock supply costs subject to resource availability, demand requirements, and biomass property constraints.

The proposed methodology has important implications to manage risks associated with feedstock availability when planning for long-term contracts of biomass supply to prevent operational disruptions at the biorefinery.

The probability model

Based on Rae (1971), let R be a probability model consisting of $R_{n,t}$ number of sub-models with *n* possible states of nature for each stage *t*. The model had five *t*-stages because it considered a five-year contract for dedicated energy crops, and the number of states of nature *n* varies over stages.

$$R_{n,t}$$

$$t = 1, \ldots 5$$

$$n = 1 \ldots j^t$$

Miscanthus and switchgrass were the two lignocellulosic energy crops considered to produce a conversion-ready feedstock for its biochemical conversion to hydrocarbons. I assumed yields can vary within the minimum and maximum limits, hence I defined *j* combinations of possible feedstock yields for each crop. Table 7 lists the combinations for the two candidate energy crops: *j* equals 1 when the probabilistic yield per acre is high for switchgrass and high for miscanthus; *j* equals *2* when the yield per acre is high for switchgrass and low for miscanthus; *j* equals 3 when the yield per acre is low for switchgrass and high for miscanthus, and *j* equals 4 when the yield per acre is low for switchgrass and high for miscanthus.

Table 6. Notation to label the yield combinations for two candidate energy crops

j[a]	Switchgrass	Miscanthus	Notation[b]
1	High yield	High yield	H_{f1} - H_{f2}
2	High yield	Low Yield	H_{f1} - L_{f2}
3	Low Yield	High yield	L_{f1}- H_{f2}
4	Low Yield	Low Yield	L_{f1} - L_{f2}

[a] *j* identified the combinations from the two sets of values of the candidate energy crops.
[b] f_1 identified switchgrass and f_2 identified miscanthus.

Each submodel $R_{n,t}$ is one node of the probability tree depicted in figure 4, where each branch represents the outcome $e_{n,j,t}$, defined as the state of nature *n* in which a yield combination *j* occurred within stage *t.* The states of nature are mutually exclusive and collectively exhaustive with associated probabilities given by the set $\pi_{n,j,t}$ which represents the probability of the state of nature *n* in which a yield combination *j* occurred within the stage *t.*

The probability model assumed that each n-state of nature affects the later outcome, hence the probabilities of stage *t+1* are conditional to the random state of nature of the prior stage *t*. At the end of the fifth stage, the outcomes of the model are the joint probabilities θn calculated as the product of the probabilities in the prior stages along the branches, where n goes from 1 to 1024. Let's recall that *n* grows exponentially with *t*, therefore

$$n = \{1\ldots j^t\} = \{1\ldots 4^5\} = \{1\ldots 1{,}024\}$$

Table 8 described a sample of states of nature and their subject probabilities. The probabilities of the states of nature for stage 1 were calculated by applying the GC method, and since the probabilities for the stage *t+1* were conditioned by prior events, notice how the probabilities were calculated accounting the prior stages. At the end of the model, in stage *t=5*, the joint probability θ_1 was calculated as the product of the probabilities of the previous stages.

Table 7. A sample of nature states and their subjective probabilities

	Description	Probabilities
Stage 1 = Year 1		
$e_{1,1,1}$	H_{f1} - H_{f2} (High yields for both switchgrass and miscanthus)	0.28
$e_{2,2,1}$	H_{f1} - L_{f2} (High yield for switchgrass and Low yield for miscanthus)	0.06
$e_{3,3.1}$	L_{f1} - H_{f2} (Low yield for switchgrass and High yield for miscanthus)	0.02
$e_{4,4,1}$	L_{f1} - L_{f2} (Low yields for both switchgrass and miscanthus)	0.64
Stage 2 = Year 2		
$e_{1,1,2}$	H_{f1} - H_{f2} on year 2, given that production yield for both feedstock in year 1 was H_{f1} - H_{f2}.	$0.28x0.28$
$e_{13,1,2}$	H_{f1} - H_{f2} on year 2, given that production yield for both feedstock in year 1 was L_{f1} - L_{f2}.	$0.64x0.28$
Stage 5 = Year 5		
$e_{1,1,5}$	H_{f1} - H_{f2} in year 5, given the occurrence of H_{f1} - H_{f2} in the previous years from 1 to 4.	$\prod_{1}^{5} 0.28^{a}$

[a] *The product function is equal to 0.28 x 0.28 x 0.28 x 0.28 x 0.28.*

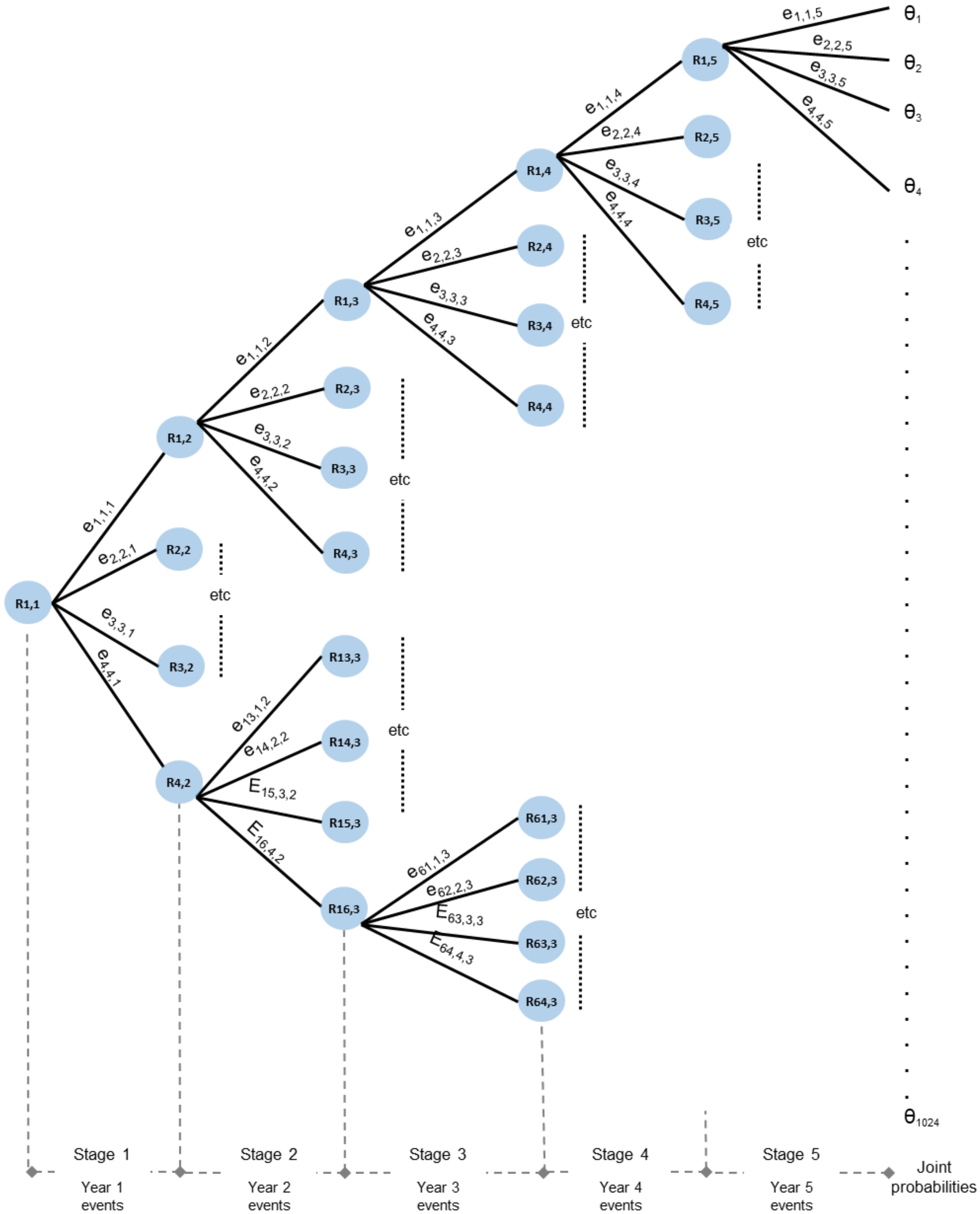

Figure 4. Probability tree diagram for 5 years of land contract

The Gaussian Cubature approach

As mentioned before, I considered four states of nature that resulted in a total of 1,024 outcomes at the end of the fifth stage. If a bigger set of options were considered, the probability model would increase in size and cause familiar dimensionality problems when there are many stages and many possible events. Since I needed an appropriate size model to be handled in GAMS without facing any computational difficulties, and compute a set of few values that would statistically represent the distribution of the production yields

To that end, I applied the Gaussian Cubature (GC) approach to calculate the values and probabilities of the maximum and minimum limits of the two lignocellulosic energy crops considered.

The GC technique developed by DeVuyst and Preckel (2007) used linear programming to generate samples with fewer points but still retaining much of the original's distribution information. I defined a vector of random variables X consisting of data for biomass yield of switchgrass (x_1) and miscanthus (x_2), such that:

$$E[g(X)] = \int_A g(X)f(X)dx \qquad \text{[Eq 1.]}$$

where $f(X)$ is the joint density function of the vector X, and $g(X)$ is the function whose expected value is to be computed.

The GC approach chooses points and probability weights such that lower-order moments of the density function maintain the lower-order moments of the original distribution for biomass yield. A GC approximation is defined by the following system of equations:

$$\sum_i \sum_m p_{i,m} \left(x_{1,m}\right)^{k_1}\left(x_{2,m}\right)^{k_2} = E\left[\left(x_{1,m}\right)^{k_1}, \left(x_{2,m}\right)^{k_2}\right];\ \forall 0 \leq k_m \geq 3, p_i \geq 0 \qquad \text{[Eq 2.]}$$

$$\sum_{i=1}^{m} p_i = 1 \qquad \text{[Eq 3.]}$$

To determine the probabilities p_i of the cubature points, I set up an optimization model based on this system of equations. After solving the model, I got the lowest and highest expected values in the GC distribution and the probabilities for the combination of those values as listed in table 6 to assume that biomass yield will vary within the maximum and minimum expected limits.

Table 8. Yield combinations for two candidate energy crops: maximum and minimum limits, and the probability for each combination

j^a	Combination	Switchgrass (tons/acre)	Miscanthus (tons/acre)	$\pi_{j,t}$
1	H_{f1} - H_{f2}	6.91	12.06	0.28
2	H_{f1} - L_{f2}	6.91	5.63	0.06
3	L_{f1} - H_{f2}	3.91	12.06	0.02
4	L_{f1} - L_{f2}	3.91	5.63	0.64

[a] *j* identified the combinations from the two sets of values of the candidate energy crops.
[b] f_1 identified switchgrass and f_2 identified miscanthus.
[c] $t=1$ for the first year.

This relatively small set of values provided reliable information from the original bivariate distribution and it was used at the beginning of stage t=1 to generate probabilistic knowledge for the posterior stages *t+1*. Consequently, the events happening on stage *t+1* would be conditioned on the prior events.

The discrete stochastic programming model

The final stage of the methodology was building a discrete stochastic programming model (DSP) to minimize the total delivery cost of biomass subject to the probability distribution of two biomass yields, compositional attributes, transport cost, and demand requirements.

The design parameters for the biorefinery were based on a conversion facility modeled by Davis et al. (2018), with an assumed annual plant capacity of 724,000 dry ton per year. The design also assumed that multiple biomass feedstocks would be delivered to a depot located alongside the biorefinery, where they would be processed into pellets, and then blended to produce conversion-ready biomass that would meet both ash and carbohydrate specifications for its biochemical conversion to hydrocarbon fuels (Roni et al., 2018). Previous research from NREL recommends that a good quality lignocellulosic biomass should have a total carbohydrate content greater or equal than 59%, and an ash content less than 5% (Kenney et al.-a, 2013).

The objective function *Z* was formulated as a cost minimization function accounting for the production cost, transportation cost, and the storage cost. I applied a 5% discount rate to have all costs in terms of the current value.

$$\min_{A_f,\, Cons_{n,f,t},\, S_{n,f,t},} Z = \left(\sum_{t=1}^{5}\sum_{f=1}^{2}\frac{\left(A_f P_f\right)}{(1+d)^t}\right) \qquad \text{[Eq 4.]}$$

$$+\sum_{t=1}^{5}\sum_{n=1}^{4^t}\sum_{f=1}^{2}\frac{Transp_{n,f} * \left(A_f * Y_{n,f} * \pi_n\right)}{(1+d)^t}$$

$$-\sum_{n=1}^{4^t}\frac{\theta_{n,5} * B_f\left(S_{n,f_1,5} + S_{n,f_2,5}\right)(1-L)}{(1+d)^5}$$

The first element of equation 4 expresses the cost of producing *A* acres of the crop type *f* at a P_f production cost in dollars per acre. The second element of equation 4 expresses the cost of moving the biomass produced in A_f acres where the yield $Y_{n,f}$ varies given the probability π of the *n* state of nature. The last term accounts for the cost of storage at the end of the fifth stage given the joint probability θ_n.

The model assigned the number of acres to grow each biomass type *f*, the consumed biomass type *f* in tons given the *n* state of nature within the stage *t*, and the unused biomass to be stored for its consumption in later years.

Production cost

Switchgrass production costs were calculated based on a switchgrass budget for biomass production prepared by Jacobson and Helsel (2014). All quantities and prices were calculated on a per-acre basis and projected for a payback period of 5 years. Miscanthus production costs were calculated based on a miscanthus budget for biomass production prepared by Jacobson et al. (2013). The average annual production cost for switchgrass was $ 200 per acre, and for miscanthus was $248 per acre, those values included the costs during the establishment year (year 1), plus soil fertility operations, weed control, and harvesting (Jacobson et al., 2013, Jacobson et al. 2014).

Transport Cost

I accounted for the biomass availability effect on the DSP model by calculating the cost of moving the biomass in terms of the volume supplied.

For this purpose, I estimated the cost to move one ton of biomass to the biorefinery as a function of the total tons of biomass available at a radial distance from that biorefinery. First, I assumed that the depot was co-located with the biorefinery and100% of the biomass projected by DOE (2016) was available. Second, I performed a regression that explained the change of a weighted average cost in dollars per ton given the increase of the biomass available on a radial distance from a biorefinery. I followed the design assumptions of Roni et al. (2018) and based on Debnath et al. (2014), I assumed that the biorefinery would be located in Okfuskee, Oklahoma, near the geographical center of three of the biorefinery locations (Lincoln, Hughes, and Muskogee counties) identified by the U.S. EPA (2010).

I selected the best fit model for both switchgrass and miscanthus. $Transp_{n,f}$ for switchgrass was formulated as a quadratic expression in terms of the total volume of biomass supplied from the farm gate to the biorefinery.

$$Transp_{n,f1} = -3E^{-12}\left(A_{f1}Y_{n,f1}\right)^2 + 3E^{-5}\left(A_{sw}Y_{n,f1}\right) + 16.652 \qquad \text{[Eq 5.]}$$

$Transp_{n,f}$ for miscanthus was formulated as a polynomial equation with the total volume of biomass supplied from the farm gate to the biorefinery as a dependent variable.

$$Transp_{n,f2} = 2.9312\left(A_{f1}Y_{n,f1}\right)^{0.2063} \qquad \text{[Eq 6.]}$$

Average transportation cost in $ per dry ton increases when the biomass volume increases because the biorefinery would be forced to collect biomass from farther locations, which would increase travel distance and the number of roundtrips needed to move the biomass.

Storage Cost

The model considers the unused biomass that would be stored for its consumption on later stages. I set the storage costs as $20 based on Duffy (2008) who reported a switchgrass storage cost of $16.67 in 2008 dollars, equivalent to $19.85 in 2020. The calculations for the storage cost assumed an enclosed type building to maintain the quality of the biomass, including the cost for the facility used, the value of the biomass in storage, plus the dry matter loss associated. The costs were calculated within the five stages considering the model was created for a five-year contract. A 15% dry matter loss during biomass storage was considered based on an INL technical report (Roni et al., 2020).

Constraints

According to the design parameters, the demand (*Dem*) was 724,000 dry ton per year during the five stages of the model. The demand constraint must be satisfied as to the biomass for consumption $Cons_{n,f,t}$ has to meet the set demand for state of nature *n,* of biomass type *f* at the stage *t*.

$$\sum_{f}^{2} Cons_{n,f,t} \geq Dem \qquad \text{[Eq 7.]}$$

If the left-hand side variable in Eq.7 is greater than the required demand, the excess of biomass supplied should be available for later stages, and therefore considered as one of the constraints.

Equation 8 limits the unused biomass within stage *t* in terms of the biomass produced from A_f acres minus the biomass needed for consumption plus the biomass available from prior stages. I assumed there is no stock from a prior stage when *t=1* because that is the time when the biorefinery started operations. Equation 8 also considers the losses due to storage on the unused biomass from the prior stage *(t-1)*.

$$(A_f * Y_{n,f}) + (1 - L)S_{n,f,t-1} - S_{n,f,t} \geq Cons_{n,f,t} \qquad \text{[Eq 8.]}$$

$$S_{n,f,0} = 0$$

Feedstock quality constraints were considered for carbohydrate content in equation 9, and ash content in equation 10. Where c_f is the minimum percentage of carbohydrate content required, a_f is the maximum percent of ash content specification, $\bar{c}_f$ is the average carbohydrate content percentage on biomass type f, and $\bar{a}_f$ is the average ash content percentage on biomass type *f*.

$$\sum_{f=1}^{2} \bar{c}_f(Cons_{n,f,t}) > c \sum_{f=1}^{2} Cons_{n,f,t} \qquad \text{[Eq 9.]}$$

$$\sum_{f=1}^{2} \bar{a}_f(\, Cons_{n,f,t}) < a \sum_{f=1}^{2} Cons_{n,f,t} \qquad \text{[Eq 10.]}$$

Equations 11, 12 , and 13 were the non-negativity constraints for the decision variables.

$$A_f \geq 0 \qquad \text{[Eq 11.]}$$

$$Cons_{n,f,t} \geq 0 \qquad \text{[Eq 12.]}$$

$$Stock_{n,f,t} \geq 0 \qquad \text{[Eq 13.]}$$

Table 9 provided the definitions of the sets, parameters, and variables used in the formulation of the discrete stochastic method.

Table 9. Summary of the definitions of sets, parameters, and decision variables used in the model

Notation		Description
Z	=	Objective function. Total cost in dollars for transporting the feedstock from the farm gate to the biorefinery.
Decision variables		
A_f	=	Acres per biomass type *f*.
$Cons_{n,f,t}$	=	Supplied biomass type *f* that will be consumed by the biorefinery given the state of nature *n* within year *t*. Units were in tons per year.
$S_{n,f,t}$	=	Unused biomass type *f* in stage t which will be stored for its consumption on stage *t+1* given the state of nature n, within stage *t*. Units were tons per year.
Parameters		
P_f	=	Cost of production in dollars per acre for biomass type *f*.
d	=	The discount rate assumed 5%.
$Transp_{n,f}$	=	Transport costs in dollars per ton of biomass type *f* given the state of nature *n*.
$Y_{n,f}$	=	Production yield in tons per acre of biomass type *f* given the state of nature *n*.
π_n	=	Probability of the state of nature *n*.
$\theta_{n,5}$	=	The joint probability of the state of nature *n* at year 5, calculated as the product of the probabilities in the prior stages along the branches.
$B_{n,f}$	=	Cost of storage in an enclosed building in dollars per ton.
L	=	Losses due to storage assumed 15%.
Dem	=	Demand in tons per year of total feedstock based on the biorefinery plant capacity assumed as 724,000 tons per year.
$\bar{c}_f$	=	Average carbohydrate content on biomass type *f* in percentage units.
c	=	Minimum percentage of carbon content required for a biomass feedstock ready for its biochemical conversion to hydrocarbons.
$\bar{a}_f$	=	Average ash content for biomass type *f* in percentage units.

Notation		Description
a	=	The maximum percentage of ash content allowed for a biomass feedstock ready for its biochemical conversion to hydrocarbons.
Set Definitions		
f	=	Set of biomass type which identifies switchgrass as f_1, and miscanthus as f_2.
n	=	States of nature defined in the probability model.
t	=	Number of stages in the probability model which considered five *t*-stages corresponding to a five-year contract for dedicated energy crops.

The last step was to run the model using the average weighted yield for switchgrass (6.65 tons/acre), and miscanthus (9.80 tons/acre) with a 100% probability to compare the results with the joint probability model.

Data

Biomass yield of switchgrass and miscanthus was collected from the public dataset provided by the National Renewable Energy Laboratory (NREL) at the Biofuel Atlas website https://maps.nrel.gov/biofuels-atlas. The data is the projected potential of biomass per year by 2030, based on an estimate that assumes market prices ≤ $60/dry ton at the farm gate ready for delivered to a processing facility (DOE 2016). Energy crop yields were empirically modeled using data from more than 110 field trails to estimate county-specific per-acre yields based on 30-year historic weather data.

The costs of production were retrieved from the PennState Extension website who published miscanthus and a switchgrass budget for biomass production. Those budgets indicated a breakeven payback period of 5 years for both crops, which fits our model for a five-year contract.

CHAPTER IV

RESULTS

The uncertainty of the biomass yield was addressed with a discrete stochastic programming model which considered the probabilities of a combination of high yield and low yield possible scenarios for two biomass candidates: switchgrass and miscanthus.

The GC method was applied to compute the values for a set of four states of nature for stage 1 of the probability model. Table 06 in the previous section showed the values for the maximum and minimum limits, and the probability for the possible combinations. According to the results from the GC method, switchgrass yield is expected to vary from 3.91 tons per acre to 6.91 tons per acre, and miscanthus yield is expected to vary from 5.63 to 12.06 tons per acre. Miscanthus production approximately doubles switchgrass yield minimum and maximum values. For the first stage of the probability model, based on the data processed with GC, the probability to get the lowest production for both feedstocks was 0.64, the probability to get the highest volume of both feedstocks was 0.28, followed by a probability of 0.06 to get high yield values of switchgrass and low yield values of miscanthus, and a 0.02 probability of low switchgrass yield and high miscanthus yield.

By setting four states of nature with the combination of the maximum and minimum values of yield, the probability model built for 5 stages, corresponding to 5 years of the contract, considered a total of 1,024 outcomes at the end of the fifth year of the contract.

The results from the DSP model showed the minimum cost of production, transport, and storage for a multiple feedstock supply that met the biorefinery assumed capacity of 724,000 tons/year, subject to the year to year yield variability and quality characteristics of switchgrass and miscanthus. The optimization model was solved in seconds using GAMS® running on a desktop computer with Intel® Core i7 3.6 GHz CPU and a 16 GB memory limit on a Windows® operating system.

Under the assumption of 100% availability of biomass projected by DOE (2016), the costs to produce, supply, and store switchgrass were $68.98 per ton on a high yield case scenario and $121.90 per ton under a low yield case scenario. Let's recall that the maximum yield value approximately doubled the minimum yield value and therefore the cost changed in the same proportion. Based on the data from DOE (2016), switchgrass projected availability is higher than miscanthus, therefore it is expected that the transportation costs of miscanthus were higher than switchgrass because the biomass is more disperse within the region and with lower availability. Table 10 also presented higher production costs for switchgrass compared with miscanthus because miscanthus had higher productivity levels when compared with switchgrass, and it is expected that higher yields led to higher productivity and lower expected costs.

Results in table 10 also showed that 71% of total land was assigned to grow switchgrass, and 29% of the total land was assigned to grow miscanthus.

Table 10. Costs for a high yield case scenario and a low yield case scenario of each lignocellulosic biomass and the blend

	High Yield scenario Cost ($/ton-year)			Low Yield Scenario Cost ($/ton-year)			Weighted average yield scenario Cost ($/ton-year)		
	Switchgrass	Miscanthus	Blend	Switchgrass	Miscanthus	Blend	Switchgrass	Miscanthus	Blend
Blend ratio	71%	29%	100%	71%	29%	100%	64%	36%	100%
Production	25.06	17.81	22.98	44.29	38.14	42.52	26.04	21.91	24.56
Transport	42.20	45.27	43.08	74.57	96.97	81.01	61.82	77.96	67.62
Storage	1.72	1.82	1.75	3.09	3.89	3.28	3.15	7.98	4.88
Totals	68.98	64.89	67.80	121.90	139.00	126.82	91.02	107.85	97.00

The model also suggested a total of 164,859 acres to meet the annual requirements of a biorefinery with a plant capacity of 724,000 dry ton per year considering all states of nature and their subjective probabilities defined in table 8. Results in table 11 suggested that 117,150 acres of switchgrass and 47,238 acres of miscanthus should be contracted per year. The model selected a higher proportion of switchgrass which has lower yield values, lower carbohydrate content, higher ash content, and lower costs compared with miscanthus. Miscanthus quality specifications were higher, but so were the costs, but the model considered both factors to select the optimal proportion of each dedicated energy crop so that the blend met the quality specifications for a biochemical process.

According to the BT16 report, Oklahoma had a total of 5.8 million acres potentially available for dedicated energy crop, therefore the total land suggested from the results represented 3% of the available land projected by DOE (2016).

Table 11. Biomass produced given the maximum and minimum values of yield

	Land (acres/year)	Low Yield (tons/acres)	High Yield (tons/acres)	Low Yield (tons/year)	High yield (tons/year)
Switchgrass	117,150	4	7	458,057	809,507
Miscanthus	47,238	6	12	265,949	559,689
	164,388	----	-----	724,006	1,379,195

The results in table 11 also indicated that the model satisfied the biorefinery demand of 724,000 tons of biomass per year even if both switchgrass and miscanthus had low yield values. In the case of high yield values, the model considered the storage of biomass excess for its consumption in the next year.

Biorefinery demand was met when considering the probabilities for each stage, see table 12 below listing the probability-weighted yields. Biomass delivered to the biorefinery for a biochemical process had to meet a maximum ash content of 5% and a carbohydrate content above 59%. Results in table 12 also showed the blend of switchgrass and miscanthus would meet both carbohydrate and ash specifications with a weighted average of 5% of ash content and 73% of carbohydrate content.

Table 12. Probability weighted yields and quality specifications

Switchgrass (tons/acre)	Miscanthus (tons/acre)	$\pi_{j,t}$ [a]	Probability weighted yield (tons/year)	Carbohydrate Content[b]	Ash content[c]
6.91	12.06	0.28	386,174.65	73%	5%
6.91	5.63	0.06	64,527.34	71%	5%
3.91	12.06	0.02	20,554.90	75%	4%
3.91	5.63	0.64	463,363.64	73%	5%
Expected yield for year *1*			934,621.53	73%	5%

[a] where $\pi_{j,t}$ is the probability of the yield combination *j* of the possible yield values occurred within stage *t* for a set of two dedicated energy crops, where *t=1* for the first year.

[b] Required minimum carbohydrate content specification: 59%

[c] Required maximum ash percentage: 5%

An additional scenario was analyzed without considering the uncertainty in biomass yield. For this case, the weighted average yield for switchgrass and miscanthus was calculated, and it was introduced into the DSP model by setting a 100% probability for a switchgrass expected yield of 6.65 tons per acre, and a miscanthus expected yield of 9.80 tons per acre.

Table 13. Biomass produced based on a weighted average production case

	Weighted Average Yield (tons/acres)	Land (acres/year)	Weighted Average Production (tons/year)
Switchgrass	6.65	102,460	681,359
Miscanthus	9.80	57,440	562,913
	----	159,900	1,244,272

This last scenario was not controlling for the year to year variability, and it was used as a reference to compare the DSP that manages that risk. The results in table 13 showed an expected 1,244,272 tons per year, which is a number still within the range showed in table 11, but the limitation of this case is the assumption of an expected biomass supply equal to a mean value during the five years of the contract.

Results in table 14 compared the final stock at year 5, the last stage of the probability model. Under the probability model, the proportion of switchgrass and miscanthus is 67% and 33% respectively. Under a weighted average yield, the proportion is 58% and 42% for switchgrass and miscanthus. The tons in stock calculated with a weighted average yield at year 5 doubled the value compared with a probability-weighted yield. The excess of biomass increases handling costs, and it may have a negative effect on biorefinery profitability.

Table 14. Biomass stock at year 5 calculated for a probability-weighted yield scenario and a weighted yield scenario

	Probability weighted yield		Weighted average yield	
	Tons in stock at year 5	Blend ratio	Tons in stock at year 5	Blend ratio
Switchgrass	444,025	67%	955,206	58%
Miscanthus	219,778	33%	684,832	42%
Totals	663,804	100%	1,640,038	100%

CHAPTER V

CONCLUSION

This research contributed as a strategy to manage risk by introducing the year to year yield variability, considering the storage of excessive biomass in year *t*, to be used in year *t+1*, and is also considered the variation in the multiple feedstock characteristics to determine the optimal land leasing scheme for a five-year contract.

Potential investors and landowners need to manage risk before making business decisions. If the probability of a range of events can be defined and measure, the information provided will be better and a risk averse attitude may change toward decision making in favor of a biobased project.

The Gaussian Cubature approach, applied to compute a set of values and probabilities that statistically represented the yield variability of two dedicated energy crops available in Oklahoma, could be and effective took for risk management. The method limited the size of probability models without sacrificing the statistical representation of data which provided an appropriate size model solved in GAMS without facing any computational difficulties.

Based on the probabilities In other words, it is more likely to have either a good or a bad year for both crops than having a good production volume for one crop and a bad production volume for the second crop.

As a recommendation for future research, the set of values provided by GC could be updated as more information becomes available, and key variables could be introduced to control other risk factors such as the variability on soil characteristics, quality specifications, and weather conditions.

Regarding the distribution of land, the model assigns a higher proportion of switchgrass given its higher projected availability. Biomass projected availability impacted the transport costs because the model was forced to select miscanthus to compensate for the lower carbohydrate content from miscanthus. It is expected that a good feedstock quality will have positive effects on biorefinery conversion yield and profitability.

The DSP model considered the maximum ash content and minimum carbohydrate content required for biochemical conversion as one of the constraints. The INL has developed the technology to blend multiple feedstocks as an alternative to address the challenges of one crop biorefineries regarding biomass availability and variability. When a blended approach is considered, it becomes another strategy to improve the supply chain.

The results supported that a DSP model and GC method could minimize the cost of lignocellulosic feedstock while managing the risk of year to year yield variability. Under the design assumptions defined in this research, the expected total cost would vary from $68.96 per ton up to $128 per ton.

Research has proved that yield varies in a range of values that are not statistically represented by a mean, but it is needed to introduce a probability model to analyze yield variation and measure the effects of this in a supply chain model. These models reduce over contracting of land and the cost to transport biomass that a biorefinery wouldn't be able to process. This type of DSP model also restricts the likelihood of idling the biorefinery and it reduces the costs involved in that.

Ass seen from the results obtained by using the weighted average yield final decisions should consider a year to year variation probability because of the inherent biomass yield uncertainty. The possibility of variation in yield during a long term period should be furthermore researched.

Roni et al. (2018) explored the blended approach as an strategy to address biomass supply chain challenges such as availability and quality for a biochemical process. The DSP model is different by using a DSP model which subject to yield variability. The results from Roni et al. (2018) were reported as $115.52 per ton for a biorefinery located in Kansas.

Beyond the scope of this study is to consider a scenario where land from the Conservation Reserve Program (CRP) could be used for growing biomass and analyze how this would change the economics of the cellulosic biomass.

Parameters, unit operations, and even entire processes are subject to change due to technology updates and scientific advances; configuration of a process is also subject to modification according to the users' needs. New technologies are being developed to address the challenges faced by the bio-industry. As a result, there is always the need to measure the effects on costs and conversion efficiency due to the modification of existing unit operations or the implementation of new ones under a risk management approach. Some of the leading pretreatment technologies could be systematically compared to decide which one fits better on an ongoing project. To perform a robust analysis, the effects of changes in the overall chain must be measured. These questions could be easily answered with a user-friendly web-based tool that could incorporate DSP, such as the Geospatial Logistics and Agricultural Decision Integration System (GLADIS) developed by Craige et al. (2016), see appendix A.

As further research and given how open source tools are becoming more reliable and innovating, an optimization platform could be integrated into an already existing framework, along with map visualizations that might be a valuable feature to implement in a web-based tool such as GLADIS.

As a final conclusion, costs can be reduced by introducing the probability model to control for the risk of yield variability and the differences in the biomass quality characteristics. Furthermore, blending approach could be another strategy to manage supply chain risks.

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APPENDICES

APPENDIX A

Craige et al. (2016) developed the Geospatial Logistics and Agricultural Decision Integration System (GLADIS), as a web-based software capable of modeling the supply chain of Oklahoma eastern red cedar, identifying potential processing facility locations, and evaluating transportation, harvesting, processing and refinement costs.

The second version of GLADIS is being developed by a research team from Biosystems Engineering Department and Agricultural Economics Department at Oklahoma State University. The second version of GLADIS is being tested to validate its user interface, reliability, and functionality to model supply chains for agricultural commodities.

Currently, GLADIS has been updated to be suitable for different crops and conversion processes, thus its appropriateness for this venture. GLADIS gives the user the flexibility to evaluate multiple scenarios and to assess the economic performance of any bioindustry raw material through sensitivity analyses and Monte Carlo simulations.

At the time of this research, there were no other bioindustry simulation programs available for public use to assess those design cases and analyze the effect of changes in one or several stages of the process into the complete process chain. Besides, GLADIS is a public use web-based tool that allows stockholders to build their simulations based on various processing technologies to assess

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